Commodity Trade Finance Risk Prediction Through Logistics Transaction Graph Inference

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Abstract

Commodity trade finance supports industrial enterprises in purchasing metals, chemicals, coal, petroleum products, agricultural raw materials, and other bulk goods. However, this financing mode is exposed to risks from false warehouse receipts, duplicated pledges, abnormal logistics records, price volatility, weak buyer credit, and inconsistent trade documents. Traditional risk models often evaluate the borrower alone and fail to verify whether financing is supported by real commodity flow and repayment capacity. This study develops a logistics transaction graph inference model for commodity trade finance risk prediction. The model builds a heterogeneous graph linking borrowers, sellers, buyers, warehouses, logistics providers, warehouse receipts, invoices, purchase contracts, collateral records, commodity prices, and repayment behavior. A graph neural encoder captures transaction credibility, while a knowledge reasoning module identifies suspicious paths such as repeated warehouse-receipt pledging, circular trade, abnormal delivery gaps, and price-driven collateral shrinkage. The dataset contains 31,800 borrowing enterprises, 118,000 trading counterparties, 760 warehouses, 1.96 million invoices, 580,000 logistics records, 86,000 warehouse receipts, and 7,640 confirmed trade-finance risk cases over 34 months. The proposed method reduces median warning time before financing deterioration from 62 days to 22 days. It identifies 9,480 suspicious logistics-transaction chains and 1,920 duplicated warehouse-receipt pledge structures. Graph aggregation reduces manual document review from 27,500 trade batches to 5,840 relation-linked investigation cases. The inference engine completes portfolio assessment in 12.9 minutes and processes 2.14 million transaction edges during each full update. The findings indicate that logistics transaction graph inference can improve commodity trade finance risk prediction by connecting credit risk with verifiable trade, logistics, and collateral evidence.

Keywords: Commodity trade finance; logistics transaction graph; knowledge graph inference; industrial finance; warehouse receipt risk; collateral verification; graph neural network.

1. Introduction

Commodity trade finance plays an important role in supporting the working-capital needs of industrial enterprises by enabling the purchase, storage, transportation, and resale of bulk commodities, including metals, chemicals, petroleum products, coal, and agricultural raw materials. Compared with conventional corporate lending, commodity trade finance involves a more complex interaction among physical goods, transaction documents, logistics activities, collateral arrangements, and multiple participating entities [1,2]. As a result, financial institutions are exposed not only to borrower default risk but also to operational and transaction-related risks, such as forged warehouse receipts, duplicated pledges, abnormal inventory movements, commodity price volatility, weak buyer credit, and inconsistencies among contracts, invoices, logistics records, and collateral documents [3,4]. Recent research has further shown that interpretable machine-learning methods can improve anomaly identification by combining predictive performance with transparent explanations of abnormal patterns, which is particularly valuable in security-sensitive and operationally complex environments [5]. In parallel, supply-chain finance studies indicate that incorporating transaction relationships, operational behavior, and inter-firm dependencies can improve risk identification beyond traditional borrower-level credit assessment [6,7]. These findings suggest that risk in commodity trade finance should be analyzed from a network and process perspective rather than through isolated financial indicators or individual transaction records [8,9].

Existing studies, however, still present several limitations when applied to large-scale commodity trade finance. First, many conventional credit-risk models treat financing applications or trade contracts as independent observations and mainly rely on financial ratios, borrower characteristics, collateral values, or historical repayment records [10,11]. Such methods have limited ability to represent dependencies among borrowers, sellers, buyers, warehouses, logistics providers, financial institutions, and pledged commodities [12,13]. Second, although graph-based learning and knowledge-graph approaches have increasingly been used in supply-chain risk analysis, fraud detection, and industrial finance, relatively few studies explicitly model the operational structure of commodity trade finance, in which warehouse receipts, invoices, transportation records, inventory status, collateral ownership, and repayment behavior must be verified jointly [14,15]. Third, abnormal behavior may propagate through multiple connected transactions. A forged receipt, repeated pledge, related-party trade, or suspicious logistics route may not appear highly risky when examined individually, but its connection with other contracts, counterparties, warehouses, or collateral records can reveal a substantially different risk profile [16,17]. Existing models often fail to capture such chain-level accumulation and propagation of risk [18,19]. In addition, many available studies rely on medium-sized or simplified datasets that do not adequately represent the heterogeneous entities, high transaction volumes, repeated financing relationships, and complex collateral structures found in real industrial trade-finance systems [20,21]. Another practical limitation is interpretability: many predictive models generate only a probability or risk score, while banks and operational reviewers require explicit evidence showing which entities, transactions, documents, or logistics relationships contribute to the identified risk [22,23].

To address these limitations, this study develops a logistics transaction graph inference model for commodity trade finance risk assessment. The proposed framework constructs a heterogeneous transaction graph that links borrowers, sellers, buyers, warehouses, logistics providers, warehouse receipts, invoices, trade contracts, pledged commodities, collateral records, and repayment behavior within a unified relational structure. By jointly modeling transaction attributes and cross-entity dependencies, the method is designed to identify abnormal financing relationships that cannot be detected effectively through isolated contract-level analysis. The graph inference mechanism further traces potential risk propagation across logistics, collateral, and trade relationships, allowing the model to distinguish localized anomalies from broader high-risk transaction chains. In addition to improving predictive accuracy, the framework emphasizes interpretable risk evidence by identifying the entities and relational paths associated with suspicious behavior, thereby supporting manual verification of duplicated pledges, inconsistent documents, abnormal logistics movements, concentrated counterparty exposure, and other operational irregularities. The significance of this study therefore lies not only in developing a more comprehensive risk-prediction model, but also in providing a practical analytical framework for connecting financial risk with real commodity circulation and transaction execution. By integrating financing, logistics, collateral, and repayment information into a unified graph-based representation, the proposed approach aims to strengthen early-warning capability, improve the detection of high-risk transaction chains, and provide financial institutions with more actionable evidence for credit review, collateral verification, post-loan monitoring, and commodity trade-finance risk management.

2. Materials and Methods

2.1 Samples and Study Area

This study used a commodity trade finance dataset collected over 34 months. The sample included 31,800 borrowing firms, 118,000 trading firms, 760 warehouses, 1.96 million invoices, 580,000 logistics records, 86,000 warehouse receipts, and 7,640 confirmed risk cases. Firms were included when borrower records, trade contracts, invoices, logistics records, warehouse receipts, collateral data, and repayment records were available. The study objects were industrial firms involved in bulk commodity trade, including metals, chemicals, coal, petroleum products, and agricultural raw materials. The dataset covered different commodity types, trade volumes, warehouse locations, repayment patterns, collateral values, and buyer credit conditions.

2.2 Experimental Design and Control Setup

Two model settings were used in this study. The experimental group used the logistics transaction graph model. This model included borrowers, sellers, buyers, warehouses, logistics firms, warehouse receipts, invoices, purchase contracts, collateral records, commodity prices, and repayment behavior. The control group used a borrower-level credit scoring model. It was based on financial indicators, firm age, registered capital, repayment history, contract amount, and past credit events. This setup was used because commodity trade finance risk is related to both borrower credit and real commodity flow. The comparison tested whether logistics records, warehouse receipts, collateral data, and trade links can improve risk prediction.

2.3 Measurement Methods and Quality Control

Data were collected from financing contracts, invoice systems, warehouse receipt files, logistics records, collateral registration data, commodity price records, payment records, and buyer credit files. Each financing case was matched with its borrower, seller, buyer, warehouse, logistics firm, invoice, purchase contract, warehouse receipt, collateral record, and repayment status. Records with missing key IDs, repeated warehouse receipt numbers, abnormal delivery dates, or inconsistent invoice amounts were checked before model training. Risk variables included delivery delay, warehouse receipt reuse, collateral value change, buyer concentration, repayment delay, and document consistency. Quality control was conducted in three steps. First, repeated warehouse receipts and repeated pledge records were removed or marked. Second, invoice amounts were compared with purchase contracts and payment records. Third, logistics records were checked against warehouse entry dates, delivery dates, and buyer information.

2.4 Data Processing and Model Formulation

The commodity trade finance data were built as a logistics transaction graph $G=(V,E)$. In this graph, V represents borrowers, sellers, buyers, warehouses, logistics firms, invoices, warehouse receipts, contracts, collateral records, and repayment nodes. E represents trade, logistics, pledge, payment, collateral, and price relations. Numerical variables were standardized before model training. Categorical variables, such as commodity type and warehouse type, were encoded. Missing numerical values were replaced by medians. Missing categorical values were replaced by the most frequent value. Node features were updated as follows:

$$h_i^{(l+1)}=\sigma\left(\sum_{r\in R}\sum_{j\in N_r(i)}\frac{1}{|N_r(i)|}W_r^{(l)}h_j^{(l)}+W_0^{(l)}h_i^{(l)}\right)$$

where $h_i^{(l)}$ is the feature vector of node i at layer l, $N_r(i)$ is the neighbor set under relation type r, $W_r^{(l)}$ is the weight matrix for relation r, and σ is the activation function. The trade finance risk score was calculated as follows:

$$R_i=\lambda T_i+\mu L_i+\eta C_i+(1-\lambda-\mu-\eta)B_i$$

where R_i is the final risk score of financing i, T_i is the trade-document risk, L_i is the logistics risk, C_i is the collateral risk, B_i is the buyer repayment risk, and λ, μ, and η are weight parameters. A higher score means a higher probability of financing deterioration or suspicious trade-chain risk.

2.5 Statistical Analysis

Model performance was measured by warning time, precision, recall, F1-score, and reduction in manual review cases. The proposed model and the borrower-level scoring model used the same training and test split. Median warning time before financing deterioration was used to assess early-warning ability. Review reduction was measured by comparing trade batches with relation-linked investigation cases. Group differences were tested with paired tests when applicable. Sensitivity analysis was conducted by removing logistics records, warehouse receipt data, collateral records, and commodity price data separately. Statistical significance was set at $p<0.05$.

3. Results and Discussion

3.1 Risk Prediction Performance

The logistics transaction graph model performed better than the borrower-level scoring baseline. The median warning time before financing deterioration decreased from 62 days to 22 days. This result shows that commodity trade finance risk cannot be assessed by borrower credit and contract amount alone. Logistics records, warehouse receipts, collateral value, buyer credit, and repayment behavior also provide early risk signals. This finding is consistent with warehouse-financing studies, which show that pledge risk, borrower credit risk, operating risk, and contract risk should be assessed together [24,25]. As shown in Fig. 1, warehouse-financing risk can be examined through a structured risk index system. This supports the use of trade, logistics, and collateral evidence in commodity finance.

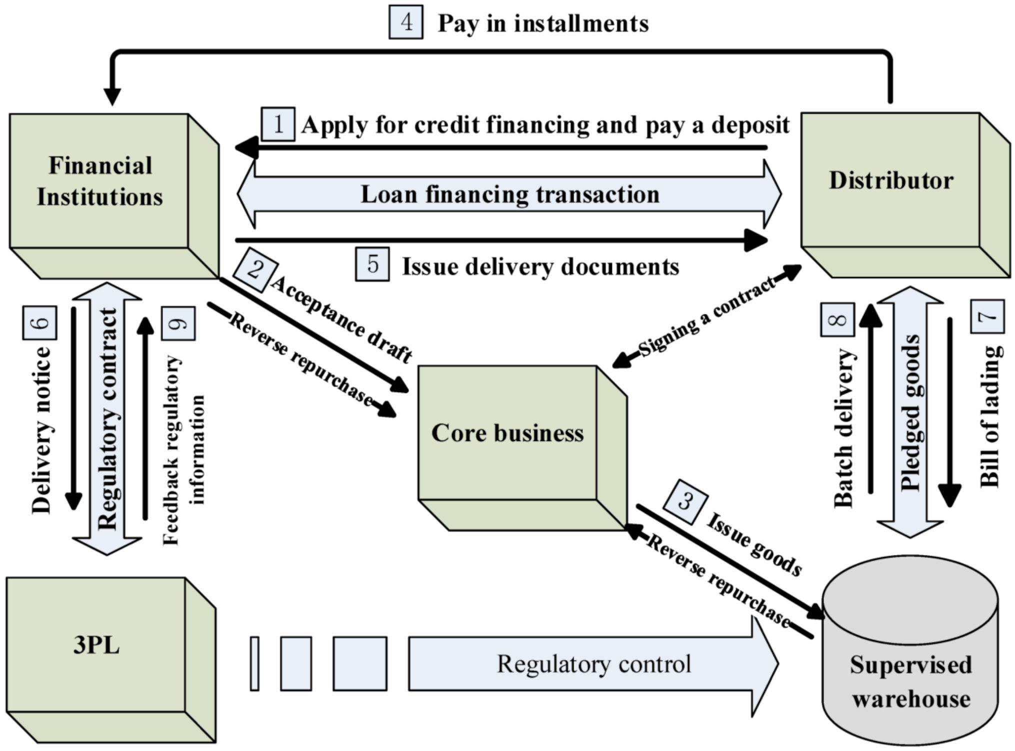

Fig. 1. Risk index system for warehouse financing using trade, logistics, and collateral information.

3.2 Suspicious Logistics-Transaction Chain Detection

The proposed model identified 9,480 suspicious logistics-transaction chains and 1,920 repeated warehouse-receipt pledge structures. These results show that trade-finance risk often appears in transaction chains rather than in single documents [26,27]. Repeated warehouse receipts were usually related to the same collateral, overlapping pledge records, or inconsistent warehouse entries. Circular trade was mainly found in closed transaction paths among related firms. Abnormal delivery gaps also suggested weak commodity control or possible false trade. Compared with document-only review, the graph method gives clearer evidence by linking borrowers, sellers, buyers, warehouses, logistics firms, invoices, receipts, and repayment results.

3.3 Review Reduction and System Efficiency

Graph-based grouping reduced manual review from 27,500 trade batches to 5,840 relation-linked investigation cases. This reduction is important because commodity trade finance often includes repeated documents, several counterparties, and shared collateral [28,29]. Traditional batch-level review may cause repeated checks and scattered evidence. By grouping related records into one investigation case, the model helps reviewers focus on high-risk chains instead of isolated files. The full portfolio assessment was completed in 12.9 minutes. The system also processed 2.14 million transaction edges in each full update. These results show that the method can support regular portfolio monitoring in practical use.

3.4 Comparison with Existing Methods and Limitations

Compared with borrower-level scoring models, the proposed method uses both credit information and trade evidence. Compared with common machine learning models, it provides clearer risk paths by linking logistics records, warehouse receipts, collateral records, commodity prices, and repayment behavior. This design fits commodity trade finance because financing safety depends on real commodity flow and collateral control [30]. Prior studies on blockchain-based warehouse-receipt platforms also show that reliable warehouse-receipt data and verified commodity records can improve trust and financing efficiency, as shown in Fig. 2. However, this study has limitations. The model depends on the quality of logistics records, warehouse receipts, collateral files, and price data. Missing or incorrect records may affect graph links and risk scores. Future studies should test the method in other commodity sectors and under incomplete data conditions.

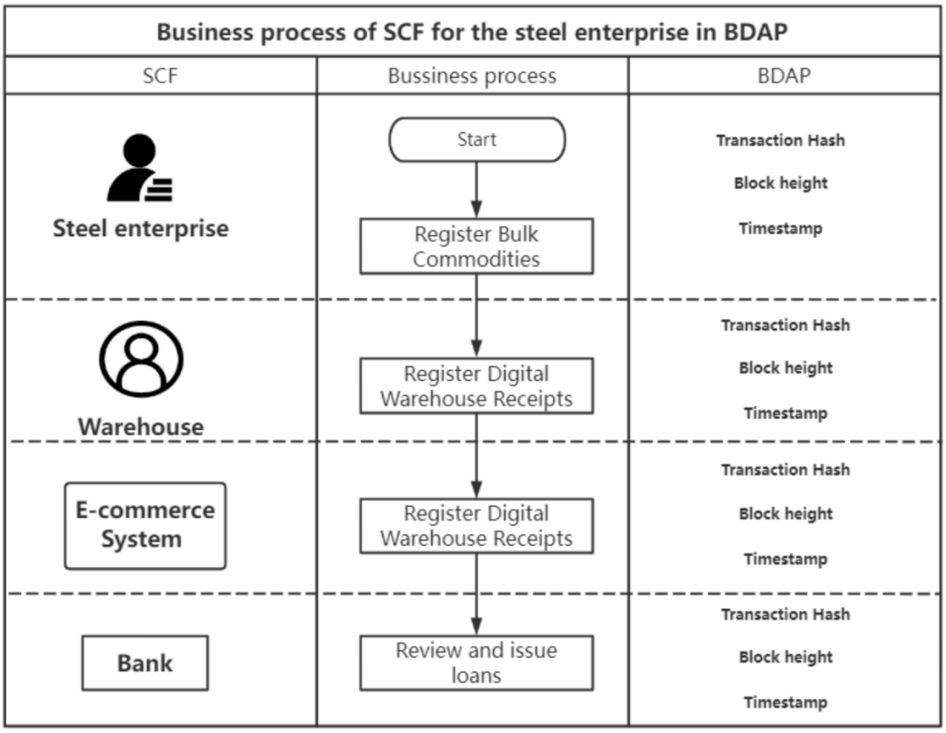

Fig. 2. Blockchain platform showing digital warehouse receipts and multi-party verification for risk control.

4. Conclusion

This study demonstrates that logistics transaction graph inference can improve risk prediction in commodity trade finance. By connecting borrowers, sellers, buyers, warehouses, logistics firms, warehouse receipts, invoices, contracts, collateral records, commodity prices, and repayment behavior, the model links credit risk with actual trade and logistics evidence. The approach reduced the median warning time before financing deterioration from 62 days to 22 days. It also detected 9,480 suspicious logistics-transaction chains and 1,920 repeated warehouse-receipt pledge structures. Manual review was reduced from 27,500 trade batches to 5,840 relation-linked investigation cases. These findings indicate that assessing trade finance risk requires combining borrower credit, commodity flow, collateral, and repayment behavior. The method supports earlier risk detection, reduces document review, and provides clearer evidence for credit decisions. Its effectiveness depends on the completeness and accuracy of logistics, warehouse receipt, collateral, and price data. Missing or incorrect records may reduce prediction accuracy. Future research should test the method in other commodity sectors and examine performance under incomplete data. Overall, this study offers a practical framework for managing trade-based credit risk in commodity finance.

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